# Gender Classification based on Local Binary Pattern and K-Nearest Neighbour

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Abstract—*Gender recognition from face image is a research area in the field of pattern recognition that determines gender based on biometric features of the face. Research has shown that the disparity between facial masculinity and femininity can be utilized to improve performances of face recognition applications in biometrics, human-computer interaction, and surveillance and computer vision. There is need to develop a gender classification system for human-computer interaction that recognizes the gender of an individual through the input face image. Hence, this study developed a facial gender recognition system using K-Nearest Neighbour (KNN). Facial images from the FERET database were obtained from the internet. The image database is made up of several images of male and female faces which have been categorized based on gender. These databases contain images of different poses for each individual. Local Binary pattern (LBP) was used to extract features of the images and the images were classified using K-Nearest Neighbour algorithm. The system was implemented using Matrix Laboratory 8.1 (MATLAB 2015a). The classification results showed that highest accuracy of 92% was achieved. The system could be adopted in classifying face images into male or female which is required in security control system or any other related systems.*

Keyword— Feature extraction, Gender, Human Computer interaction, K-Nearest Neighbour algorithm Local Binary pattern (LBP) face classification, training and testing

## 1 INTRODUCTION

Gender classification has become an area of extensive research due to its increasing application in the existing Human-Computer Interaction (HCI) system such as gender detection, face recognition, body tracking, ethnicity identification, security industry, collecting demographics, and psychology among others (Muhammad, Sheraz and Naveed, 2013). Gender classification aimed at designating an image of a person into one of the categories of male or female. Precise image -based gender classification could have central value in Human-Computer Interaction HCI (Rodrigo, Javier and Mauricio, 2006). Gender classification is also a useful pre-processing step for face recognition since it is possible to have a case of equal amount of both genders, separating both genders before the recognition process can make the process almost twice as fast.

The face is the most significant component of the human body that are normally used by humans to recognize each other; thus, facial images are the most common biometric characteristics used for human verification and identification. Facial images have gained its importance due to its use in various aspects of life such as in airports, law enforcement applications and security systems. Face detection acts as a pre- processing step for gender classification that determines the gender of an individual. The detection of regularities and affinities in different parameters of a dataset serves as a useful tool for decision making and drawing predictions (Muhammad *et al.*, 2013).

Some works had been done in the field of gender determination; some of these works are summarized in this section. Bing *et al.*, (2011) proposed a novel gender classification framework, which utilizes not only facial features but also external information, i.e. hair and clothing. Instead of using the whole face, five facial components such as forehead, eyes, nose, mouth and chin were used, also, a feature extraction method for hair and clothing was designed; these features have seldom been used in previous work because of their large variability.

For each type of feature, a single support vector machine classifier was trained with probabilistic output. The outputs of these classifiers are combined using various strategies, namely fuzzy integral, maximal, sum, voting and product rule. The major contributions of this paper were the investigation of the gender discriminative ability of clothing information and using facial components instead of the whole face to obtain higher robustness for occlusions and noise. Furthermore, hair and clothing information were exploited to facilitate gender classification. Expermental results showed that the proposed framework improves classification accuracy, even when images contain occlusions, noise, and illumination changes were used.

Rutuja and Shelke, (2015) presented a novel face detection and gender determination strategy in color images under non uniform background which uses features of the lip and the mouth region. This was done by detecting the human skin regions in image given and detecting facial features based on the measurements in pixels. The proposed method converted the RGB image into the YCbCr color space to detect the skin regions in the facial image. But in order to detect lips and mouth features, the colour images were converted into gray scale image. Here, feature extraction was carried out by using Principal component analysis (PCA) and Gabor wavelet. The results using a training database of 15 male and 15 female images show an average performance of 88.6% correct gender determination on images from test set.

Hadeel and Mohamed, (2013), also presented a technique for gender determination using eye images, the proposed technique consists of several steps cropping the eye area from the image, applying 2D-Wavelet Transform, Gray Level Co-occurrence Matrix and Discrete Cosine Transform feature extraction algorithms. Finally, support vector machine was used for the feature classification. The proposed method obtained accuracy rate of 99.49 % on gender recognition using 2D-Wavelet Transform, accuracy rate of 98.49 % on gender recognition using GLCM and 99.62 % with DCT on Faces94 database.

Saatci and Town (2006) experimented with a SVM that was trained with the features extracted by an Active Appearance Model (AAM). They had a two phase classifier. First the expression of the face was classified (categories: happy, sad, angry, neutral, and unrecognized). Then a gender classifier that was specific to the expression was used to recognize gender. This way they aimed to improve gender classification rate. However, the gender classification rate was decreased although they were able to improve facial expression classification rates by having separate expression classifiers for both genders. They suggested that the reason for the decrease in gender classification task was in the small amount of training images.

Anushri, Asif and Bhupesh, (2013) also presented a novel method to gender classification using a new simple feature extraction which extracts geometric features such as distance between eyebrow to eye, eyebrow to nose top, nose top to mouth, eye to mouth, left eye to right eye, width of nose, width of mouth. Viola Jones and Artificial Neural Network algorithms were used for feature extraction.

The features set was applied to three different applications: face recognition, facial expressions recognition and gender classification, which produced the reasonable results in all database. These features provide input to trained neural networks. The neural networks were also used for classification purpose. The networks have been trained to produce value 1 for male and 0 for female. Output of these neural networks determined the gender of the person. The results using training database of 100 male and 100 female images shows that SVM has an accuracy of 76.82% while Threshold Adaboost has an accuracy of 75.26%, a combination of LBP and SVM gave an accuracy of 81.45 % while ANN showed the best accuracy of 98.40%.

Ramin, Robert, Won-Sook and Daniel, (2015) presented a complete framework for video-based age and gender classification which performs accurately on embedded systems in real-time and under unconstrained conditions. A segmental dimensionality reduction technique using Enhanced Discriminant Analysis (EDA) was used to reduce the memory requirements up to 99.5%. A non-linear Support Vector Machine (SVM) along with a discriminative demographics classification strategy was also exploited to improve both accuracy and performance of the gender classification system.

Research has shown that the disparity between facial masculinity and femininity can be utilized to improve performances of face recognition applications in biometrics, human-computer interaction, surveillance and computer vision. However, in a real-world environment, the challenge is how to deal with the facial image being affected by the variance in factors such as illumination, pose, facial expression, occlusion, background information and noise. This is then also the challenge to the development of a robust face-based gender classification system that has high classification accuracy. Hence, there is need to develop a gender determination system using Bayesian classifier to distinguish between male and female.

## 2 METHODOLOGY

The block diagram of the gender recognition system is shown in figure 1. Face images were acquired online from the FERET database and the images were divided into two: training and testing. One hundred images were used for training (50 males and 50 female) and 50 images were used for testing (25 males and 25 female). The features were extracted using Local Binary Pattern and KNN was used to classify the images into either male or female.

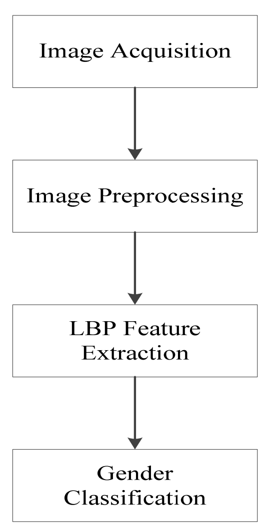



Figure 1: Block diagram of the gender recognition system

***Data Acquisition***

Facial images used to train and test the system was retrieved from the FERET database. A total of 150 images were used to train and evaluate the performance of the developed system. One hundred images were used for training and fifty images for testing.

***Image Preprocessing***

Image preprocessing helps to enhance the quality of the facial images, to improve its visual appearance and to further convert the image to a form better suited for gender classification. The preprocessing stages that was used for the developed system are image resizing, grayscale conversion and image enhancement.

**Image Resizing:** This was carried out to confirm uniformity of the facial images to be used; all the images were scaled to a uniform size. The images were resized to 100 × 100 pixels for the developed system. The *imresize* MATLAB function was used to resize the image.

**Grayscale Conversion:** The images retrieved from the online database were all coloured images. Coloured images increases processing time because of the size, also some relevant features may be hidden from coloured images, hence there is need to convert the coloured images to grayscale. The *rgb2gray* MATLAB function was used to convert the coloured images to gray images.

**Image Enhancement:** Image enhancement techniques help to highlight certain features of interest in an image. Histogram equalization was used for image enhancement. Histogram equalization is a spatial domain method that produces output image with uniform distribution of pixel intensity means that the histogram of the output image is flattened and extended systematically. Histogram equalization usually increases the global contrast of the processing image. The MATLAB function used was the *histeq*. Figure 2(a) and (b) shows an input image with the histogram before and after enhancement while Figure 3 and 4 shows the graphical respresentation of the histogram images.

a. Input image b. Enhanced image

Figure 2: Input image before (a) and after enhancement (b)

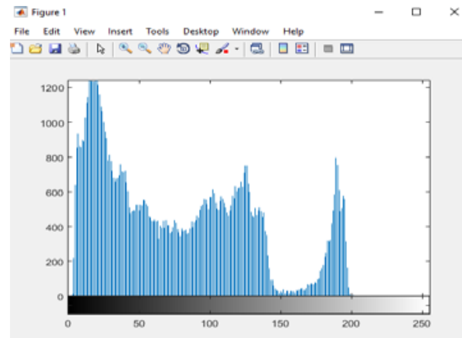



Figure 3: Histogram before enhancement

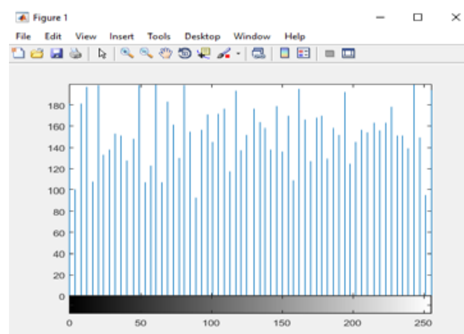


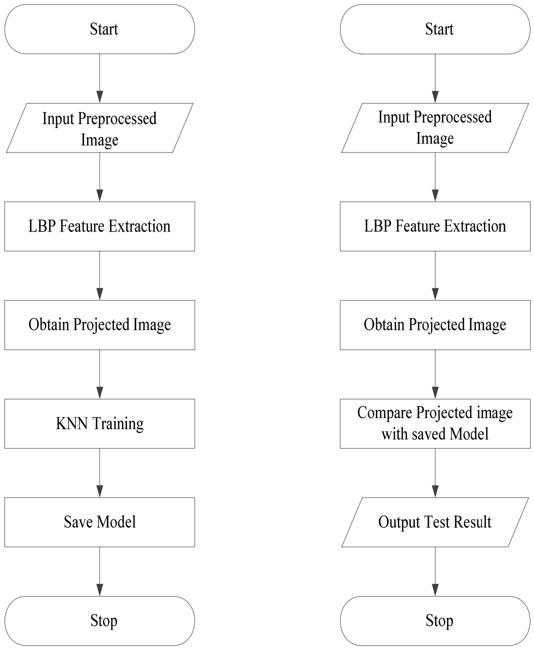

Figure 4: Histogram after enhancement

***Feature Extraction***

In the feature extraction stage, relevant features needed for recognition was extracted from each face image. The feature extraction used was the Local Binary Pattern (LBP). LBP was used to extract the texture characteristics of the face images. Using the LBP operator, the face image was divided into 3 × 3 and the local binary pattern histograms were computed and concatenated into a single histogram. The texture of the facial regions was encoded by the LBP while the shape of the face is recovered by the concatenation of different local histograms.

***Classification***

KNN classifier was used to classify the face images into either male or female. The classification is divided into training stage and testing stage. For the training stage, a KNN model was constructed from the training images and finds relationships between the predictors and targets. The testing stage tests the KNN model on a test sample whose class labels are known but not used for training the model. Figure 5 (a) and (b) shows the training and testing stages.




(a) KNN Training (b) KNN Testing

Figure 5: Training and testing stages

## 3 RESULT DISCUSSION

The results obtained from the KNN classification with a training sample of 100 images and testing sample of 50 images showed a training time of 3.396974 seconds and testing time of 4.162747 seconds. The value of K was varied between 2 to 10 and the result gotten was shown in Table 1. It was observed that the highest accuracy was 92% at K = 9 was obtained. Figure 6 represent correct classification of a female, figure 7 depicts correct classification of a male while figure 8 shows a male misclassified as a female.

| K | TP | TN | FP | FN | CC | IC | ACC (%) |
|---|---|---|---|---|---|---|---|
| 2 | 20 | 21 | 5 | 4 | 41 | 9 | 82 |
| 3 | 19 | 22 | 6 | 3 | 41 | 9 | 82 |
| 4 | 19 | 22 | 6 | 3 | 41 | 9 | 82 |
| 5 | 19 | 23 | 6 | 2 | 42 | 8 | 84 |
| 6 | 21 | 22 | 4 | 3 | 43 | 7 | 86 |
| 7 | 21 | 24 | 4 | 1 | 45 | 5 | 90 |
| 8 | 20 | 23 | 5 | 2 | 43 | 7 | 86 |
| 9 | 21 | 25 | 4 | 0 | 46 | 4 | 92 |
| 10 | 20 | 24 | 5 | 1 | 44 | 6 | 88 |

Table 1: Results of the developed system

Where TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative
CC = Correctly Classified
IC = Incorrectly Classified
ACC = Accuracy

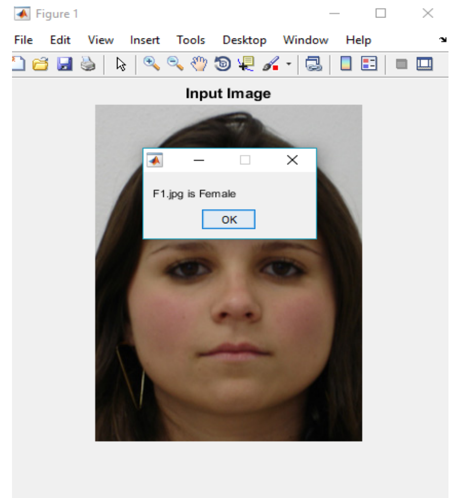



Figure 6: Correctly classified Female face

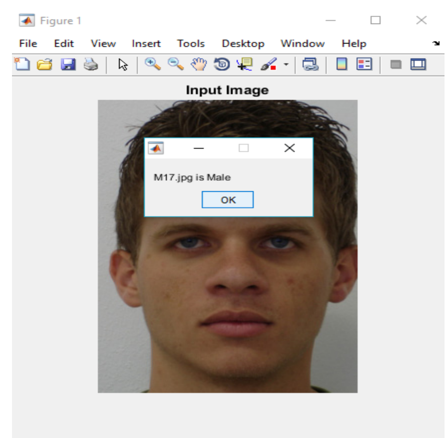



Figure 7: Correctly classified male face

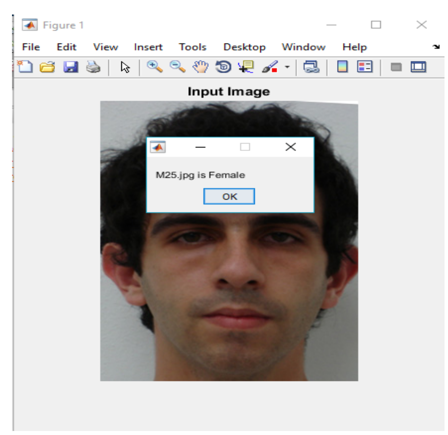



Figure 8: Incorrectly classified male face classified as female

## 4 CONCLUSION

A gender recognition system to discriminate gender from face images, with an improved accuracy was developed. An accuracy of 92% was achieved from the study which shows that the system is reliable and can be used for gender classification in any human computer interaction field. This can assist as a security measure and access control unit and hospitals.

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